Machine learning and deep neural networks: applications in patient and scan preparation, contrast medium, and radiation dose optimization

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Machine Learning and Deep Neural Networks

Applications in Patient and Scan Preparation, Contrast Medium, and Radiation Dose Optimization

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Abstract: Artificial intelligence (AI) algorithms are dependent on a high amount of robust data and the application of appropriate computational power and software. AI offers the potential for major changes in cardiothoracic imaging. Beyond image processing, machine learning and deep learning have the potential to support the image acquisition process. AI applications may improve patient care through superior image quality and have the potential to lower radiation dose with AI-driven reconstruction algorithms and may help avoid overscanning. This review summarizes recent promising applications of AI in patient and scan preparation as well as contrast medium and radiation dose optimization.

Key Words: artificial intelligence, radiation dose, reconstruction algorithms, scan preparation, cardiothoracic imaging

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Machine learning (ML) describes the construction of analytical models and decision rules on the basis of training data to perform specific tasks in complex and often voluminous datasets with or without labeling.[1,2] The ML toolset has grown large including a multitude of different mathematical models. Deep learning (DL) or deep convolutional neural networks are a specific type of ML inspired by the way the human brain processes data. This subclass of ML uses multilayered neural networks, enabled by large-scale datasets and hardware advances such as graphics processing units.[1,2] These algorithms have shown the potential to perform in a multitude of tasks such as image and speech recognition, as well as image interpretation in a variety of applications and modalities.[3–5] In the context of medical imaging, ML, and DL have so far been mainly applied to image processing, such as segmentation of relevant anatomic structures, automated measurements, interpretation, and enhancement of clinical decision-making.[1,2,6] However, ML and DL may also support the image acquisition process, may reduce noninterpretable imaging studies and lower radiation dose, and may also optimize image quality, which will be the topic of the present review.

PATIENT SCHEDULING AND PROTOCOL SELECTION

In the past 20 years, imaging study protocol selection has shifted from protocolling sheets to a paperless, fully digital protocol selection process. The electronic health record represents an overwhelming source of information, including ordering information, patient history, laboratory parameters, and previous imaging studies. Reading and sorting all this information is a time-consuming, yet important task. On the basis of knowledge about each patient, the radiologist must appropriately select or create study protocols. Recent studies showed that ML algorithms utilizing information extracted from study indications could be utilized to select appropriate imaging protocols.[7,8] Brown and Marotta[7] showed that the prediction of magnetic resonance imaging (MRI) protocols and examination priority is feasible applying natural language processing models. In another study, Brown and Marotta[8] compared 3 different ML models—support vector machine, gradient boosting machine, and random forest—to a baseline model that predicted the MRI protocol at the sequence-level for all observations. Here, the gradient boosting machine model outperformed the other models yielding a high accuracy (95%) and precision (86%).[8] Taking into account protocol/imaging study susceptibility for sequence repeats, patient age, and the information provided by previous imaging studies, future applications may use these algorithms to determine optimal time slots for the various scan protocols and the need for and type of contrast media application. This information could be used to schedule patients immediately after the scan has been requested and even before a radiologist decided which scan protocol should be used. The correct prediction of scan protocols and scan length may help optimizing scanner utilization and scheduling the appropriate amount of staff for shift coverage.[6]

PATIENT PREPARATION: IMPLEMENTATION OF A 3-DIMENSIONAL (3D) CAMERA FOR OPTIMIZED PATIENT POSITIONING

Vertical patient off-centering of only 20 mm in either direction causes significant organ dose changes in chest computed tomography (CT) performed with automatic tube current modulation because of overestimation or underestimation of the patient size from the localizer radiograph (topogram, scout view).[9] Recently, a combined color/depth 3D camera (Fig. 1) enabling automatic table positioning was introduced (Siemens Healthineers, Forchheim, Germany).[10] The 3D depth sensor of the camera employs infrared light and the time-of-flight principle to measure the distance of objects to the camera. Afterwards, an artificial intelligence (AI)-based algorithm detects anatomic landmarks in the camera data and fits a model of the most likely virtual patient avatar to the 3D data, with the virtual patient being based on data from a training population.[10,11] To set

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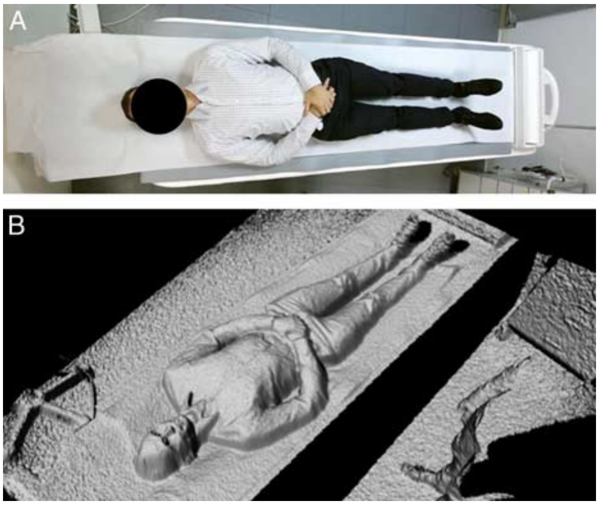

FIGURE 1. Implementation of a 3-dimensional (3D) Camera. The 3D depth sensor of the camera employs infrared light and the time-of-flight principle to measure the distance of objects to the camera (A). An artificial intelligence-based algorithm fits the data of body landmarks and depth data to a virtual patient avatar. The Avatar hull is computed and the table height at which the 3D camera planning image was taken is then adjusted such that the Avatar center and thus the patient is aligned in the isocenter of the computed tomography scanner (B). full color online

the vertical table position, the geometric center of the avatar hull is computed for the selected scan range and the table height at which the 3D camera planning image was taken is then adjusted such that the virtual patient avatar is aligned in the isocenter of the CT scanner. Saltybaeva et al[10] showed that this clinical, AI-based application of individualized and automatic patient positioning using the 3D camera allows for more accurate patient centering as compared with manual positioning by technologists, which improves radiation dose utilization and image quality. On the basis of the detected anatomic landmarks, the operator may be warned in case of patient positioning inconsistent with the selected scan protocol (eg, head first instead of feet first), and scan ranges (eg, for scans of the thorax) may be proposed. Future directions of the application of a 3D camera in cardiothoracic radiology may include virtual guidance for ECG electrode placement implementing virtual fusion of prior scans on the basis of acquired patient body landmarks and needle guidance for lung biopsy by virtual fusion of body landmarks with the planning scan. To perform a virtual topogram, obviating the acquisition and radiation dose of a conventional localizer radiograph, the system has to learn to correctly identify the position of internal organs to allow for a reasonable radiation dose modulation considering the unique patient anatomy. The 3D camera is commercially available and is used in many institutions so far. Unfortunately, it is not yet applicable to pediatric radiology.

SCAN OPTIMIZATION: ASSESSMENT OF OVERSCANNING

Especially for technologists with little experience, the scan length is often over-estimated to not miss any valuable information.[12] This practice leads to an unnecessary additional radiation exposure. Schwartz et al[12] reported that caudal overscanning in chest CT occurred in 147 of 600 scans in 6 different hospitals (4% to 60% of cases), leading to increased organ effective doses in the upper abdomen by up to 14%. Recognizing anatomic landmarks with a 3D camera mentioned above[10,11] may assist in choosing the optimal individual scan range for each patient, while neural networks may assist in monitoring and awareness of overscanning, potentially lowering the frequency of overscanning and thus decreasing unnecessary radiation exposure.[13]

Poor image quality may have a variety of avoidable reasons. Unrecognized metal parts such as necklaces or belts may cause artifacts, as well as patient motion, breathing, and swallowing. Insufficient radiation exposure, insufficient coverage or missing contrast enhancement may make a rescan of the patient necessary. A future application of ML and DL may be to recognize metal parts on the topogram and subsequently trigger dual-energy CT scanning to provide monoenergetic images for metal-artifact reduction[14] or to trigger automatic image reconstruction with metal-artifact reduction algorithms.[15] Furthermore, AI algorithms may recognize motion artifacts, insufficient coverage, missing contrast enhancement and even poor image quality in general, assisting technicians to correct such errors before finishing the imaging examination.[16] Occasionally, suboptimal or even nondiagnostic images are not recognized by technicians and the patient may have left the department for hours until the radiologist reads the scan. In these cases, AI may alert the technician to repeat the acquisition of the CT scan or magnetic resonance sequence to avoid rescheduling the patient. Esses et al[16] showed that automated image quality evaluation of T2-weighted liver MRI-sequences utilizing a DL architecture is feasible. However, this study also showed current limitations, as the overall case number in this study was low and the AI-algorithm flagged some cases as false-positives. Subsequently, these cases have again to be reviewed by a technician.[16]

PERSONALIZED CONTRAST MEDIA APPLICATION

In computed tomography angiography (CTA), scan timing is important and, together with the contrast injection protocol, the decisive factor that determines the quality of the study.[17,18] Two different bolus-timing techniques are available: delay estimation from a test bolus injection and real-time bolus tracking. Using the test bolus technique, the circulation time of each patient is determined individually by sequential scanning of the artery of interest using a test bolus of 10 to 20 mL of contrast media.[19] This scan assesses the individual cardiovascular circulation before CTA at the expense of an additional test bolus CT scan and an increased volume of injected contrast media. The real-time bolus-tracking technique sequentially monitors the density in an artery of interest while the contrast media bolus is injected. As soon as the predefined attenuation threshold (eg, 100 HU) has been reached the CTA scan will start after a predefined posttrigger delay.[18] This technique has the advantage of being robust in a clinical setting, it does not require the additional application of contrast media and is less time-consuming compared with the test-bolus technique. However, it has the disadvantage that the same, fixed and predefined posttrigger delay is used for all patients, not taking into account individual cardiovascular parameters such as the cardiac output. Previously, an ML-based algorithm was introduced which considers individual differences of the cardiovascular circulation in each patient (Fig. 2).[18,20] This algorithm uses the first few

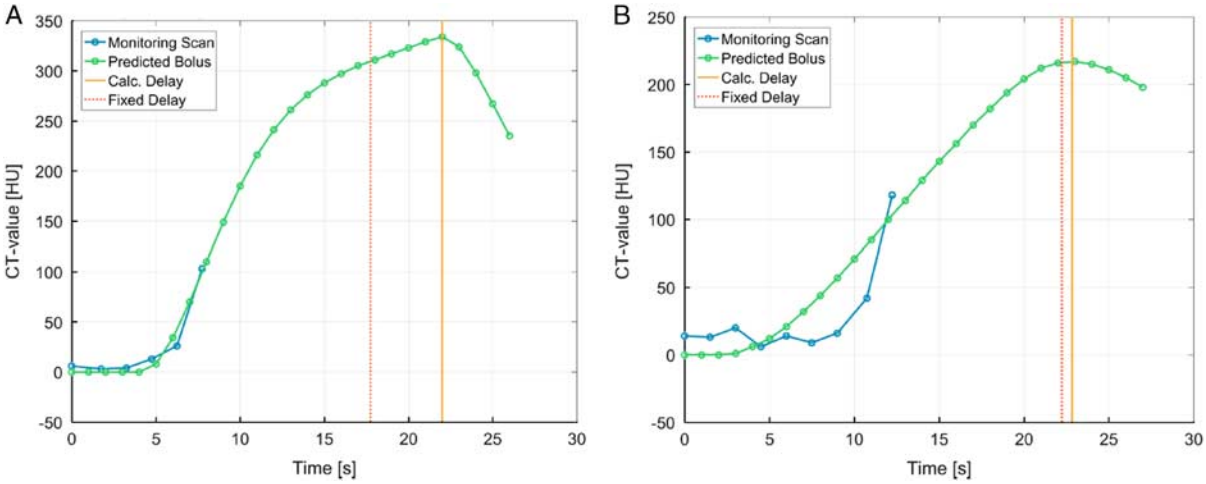

FIGURE 2. Personalization of bolus-tracking in computed tomography (CT) angiography. Graphs showing bolus-tracking signal intensity curves for CT angiography for 2 patients. Patient-specific individualized trigger delay is based on prediction of local contrast enhancement over time while considering scan parameters such as relative monitoring position, scan range, and pitch of scanner, as well as a patient-specific arterial impulse response. A, An optimal prediction of the bolus (green) based on monitoring scan data (blue). B, A wrong match of the bolus prediction and the monitoring scan data due to a steep increase of enhancement. In this setting, a fixed posttrigger delay will result in missing the peak enhancement for CT angiography.

bolus-tracking scans to analyze the patient-individual onset of the enhancement curve in real-time and match it to the most likely enhancement curve from a large database of expected enhancement curves in different injection protocols. It then calculates and adjusts in real-time the patient-specific posttrigger delay to reach optimum peak enhancement.[18] This technique showed its robustness in cardiac and thoracoabdominal CTA studies resulting in an improved and constant image quality compared with a fixed posttrigger delay, yielding a uniform contrast attenuation of the thoracoabdominal aorta independent of the cardiovascular situation of the individual patient.[18,20] The personalized bolus-tracking permits also diagnostic CTA examinations despite slower injection rates and less iodine in CTA of the abdomen.[20] The software for personalized contrast media application described above is not yet commercially available.

RADIATION DOSE REDUCTION

The tremendous developments of CT technology in the past years have led to an increase in the number of CT examinations performed worldwide. This was paralleled by fears of an increased radiation dose applied to the general population. Even though several techniques for dose optimization have been implemented, the most effective way to reduce radiation exposure is to use x-ray based imaging only when the benefits outweigh their potential risks. AI may support this decision-making with advanced possibilities to create risk stratification models, which potentially find their way in future guidelines of patient risk stratification.[21]

Optimization of CTA protocols aims towards the reduction of radiation dose and contrast medium volume application. Both can be achieved using low tube voltage protocols. Low tube voltage protocols increase the iodine attenuation because the x-ray output energy is closer to the iodine k-edge of 33 keV.[17] However, low tube voltage also increases image noise and is more susceptible to beam hardening artifacts which may compromise the accuracy.[17] Iterative image reconstruction algorithms have been introduced to reduce image noise with the potential drawback of unfamiliar noise texture leading to unnatural image appearance (plastic-like images) and excessive time for image reconstruction in some realizations, particularly when used with a too high level.[22] Recently, AI-based image noise reduction has gained attention as a potential alternative to iterative reconstruction.[23,24] One application is image space-based reconstruction in which convolutional neural networks are trained with low-dose CT images to reconstruct routine-dose CT images[24] or to optimize iterative reconstruction algorithms.[25] The potential of AI-based image denoising, in particular with regard to maintained low-contrast detectability at reduced radiation dose, will still have to be demonstrated.

Another method to decrease radiation dose in CT is a sparse sampling of CT data, comparable to compressed sensing techniques applied in MRI. Few-view or reduced angular coverage is considered to either lower radiation dose or to increase temporal resolution (eg, in respiratory-gated or electrocardiography-gated CT studies). This technique has regained interest with the growing development of novel reconstruction methods as well as increasing computational power. Lee et al[26] applied the DL technology in 3 domains—the sinogram domain, the image domain, and a hybrid domain (a combination of sinogram and image domains) and developed a DL-based sparsely sampled reconstruction technique that can produce high-quality images in a shorter time than conventional techniques. However, unlike magnetic resonance, the acquisition principle of today's medical CT scanners does not support the easy implementation of sparse sampling.

The potential of AI-based reconstruction algorithms to improve the image quality of CT studies, allowing for further reduction in radiation dose and contrast media application while speeding up reconstruction times, will have to be proven in the coming years.

AI IN MRI DATA RECONSTRUCTION

MRI often is associated with relative long acquisition times due to data sampling in the k-space but not in the image space.[27] The k-space contains spatial-frequency information that is acquired sequentially and anywhere from 64 to 512 lines of data needed for high-quality reconstructions.[27,28] The speed at which k-space can be traversed is limited by physiological and hardware constraints.[27,28] One recent innovation to overcome slow acquisition times is compressed sensing-based MRI.[27] Assuming the data is compressible, compressed sensing-based MRI allows for aggressive undersampling by performing nonlinear optimization on randomly undersampled raw data.[27,28] Applying a generative adversarial network-based model, Yang et al[28] showed that this method provides superior reconstruction with preserved perceptual image details, compared with conventional compressed sensing-based MRI reconstruction methods and previously introduced DL approaches. They could show that each image was reconstructed in about 5 ms, suitable for real-time processing.[28] Implementing AI-based compressed sensing reconstruction of MRI-sequences may be beneficial for any studies potentially susceptible for motion artefacts and especially for cardiac and lung MRI.

OUTLOOK

AI applications have the potential to optimize patient flows through departments, guiding how people perform imaging scans, and improving image quality. The automatic recognition of scan range and patient centering may reduce radiation dose and the automated recognition of imaging planes may guide inexperienced technicians in the acquisition of high-quality scans. However, even though initial results are exciting many steps need to be undertaken for these various approaches to be translated into everyday clinical practice with a diversity of software and hardware solutions. Even if strict multiple split-sample regimens are used for ML validation, multicenter evaluations will be essential to demonstrate the generalizability to various imaging sites.

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